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EVALUATION OF A METHOD FOR SHORT-RANGE FORECASTING OF EVAPORATION DUCT HEIGHTS

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Naval Environmental Prediction Research Facility

AUGUST 1981

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A method for forecasting evaporation duct heights over periods of three to twelve hours is evaluated by comparing skill and threat scores to persistence scores. Although the evaluation of data from two ocean weather stations in the North Atlantic reveals an apparent advantage of the forecast method over persistence, an analysis of variance shows no statistically significant differences between the two sets of scores.

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CONTENTS

A

1. INTRODUCTION

This study evaluates the skill of a forecasting method* that utilizes surface-observed meteorological variables to develop short range (3-12 hr) predictions of evaporation duct heights. Although this method was developed for use in short range statistical terminal forecasting, its adaptation to duct height prediction required only the selection of appropriate predictors and individual internal transformations.

Data from two ocean weather stations (OWS) in the North Atlantic Ocean, OWS Charlie and OWS Echo, were used in the evaluation, the former to represent the higher latitudes and the latter to represent the midlatitudes. For purposes of this evaluation, skill and threat scores derived from these data were compared to persistence scores.

The forecast method, the OWS data samples, and the evaluation procedure are described in Section 2. Results are discussed in Section 3. Threat and skill scores are defined in the Appendix.

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*Developed by Dr. R. G. Miller, Techniques Development Laboratory, NOAA, Silver Spring, MD 20910.

2. FORECAST METHOD

2.1 INTRODUCTION

Forecasters presently use a combination of climatology, persistence, and data on the existing synoptic situation, to develop short range (1-12 hr) weather predictions. Indications of the existing synoptic situation, in turn, can be found in certain meteorological variables observed at the surface every one to three hours.

Using this premise that surface observables can provide valid synoptic predictors, Miller (1979) designed a conditional climatological prediction method for short range forecasting based on a technique called regression estimate of event probability (REEP).* Applying the basic Markovian process to the REEP, Miller expanded the technique to develop hourly forecasts for one to twenty-four hours; these forecasts are the event probabilities determined by the regression equations, converted to categorical forecasts by a set of threshold probabilities.

It was reasonable to extend this method to the prediction of evaporation duct heights, insofar as these ducts are surface layer phenomena.

2.2 DISCUSSION

As an example, consider attempting to forecast winds and pressure using only these same variables as predictors. Wind speed (WS), wind direction (WD) and sea level pressure (P) are transformed into (0,1) dummy variables where the value is set equal to 1 if the observation falls within the dummy's prescribed interval, and to 0 otherwise. A possible transformation would be the following:

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*See Miller, 1964.

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<u>Variable</u>

P (mb)	P_1 (50-990), P_2 (990-1000), P_3 (1000-1010)
	P_4 (1010-1015), P_5 (1015-1020), P_6 (1020-1100)
WS (kt)	WS_1 (0-4), WS_2 (4-8), WS_3 (8-12)
	WS_4 (12-20), WS_5 (20-30), WS_6(30-100)
WD	WD_1 (N-E), WD_2 (E-S), WD_3 (S-W), WD_4 (W-N)

These three variables are then transformed into 16 (0,1) dummy variables; if the observed P is 1013, then $P_4=1$, and for all other i's, $P_i=0$. Wind speed and direction are set in like manner. A regression equation is then calculated for each of the dummy variables.

Using all 16 dummies as predictors, Miller (1979) has shown that this method gives probabilities directly from the regression equation, such that

$$P[P_1=1] = a_0 + \sum_{i=1}^{16} a_i z_i. \tag{2-1}$$

$P[P_1=1]$ is the probability that P_1 (i.e., pressure is between 950 and 990) equals one; a_i are the regression coefficients, and Z = (0010 . . . . 0) is a vector whose components are 1 if the observed P, WS, and WD occur with the given range and are 0 if not.

There are 16 such regression equations,

$$P[P_1=1] = a_{01} + \sum_i a_i z_i$$

$$\vdots$$

$$P[P_{16}=1] = a_{0,16} + \sum_i a_{i,16} z_i$$

The coefficients can be represented by a 16x16 matrix $\underline{0}$.

$$\underline{0} = \begin{pmatrix} a_{0,1} & a_{1,1} & a_{1,2} & \cdots & a_{1,16} \\ a_{0,2} & a_{1,2} & a_{2,2} & \cdots & a_{2,16} \\ \cdot & & & & \cdot \\ \cdot & & & & \cdot \\ \cdot & & & & \cdot \\ a_{0,16} & a_{1,16} & & \cdots & a_{16,16} \end{pmatrix}$$

so that

$$\underline{P} = \underline{Z} \cdot \underline{0}, \quad \text{where} \tag{2-4}$$

$$\underline{P} = (P_0 P_1 \ . \ . \ . \ P_{16}) \tag{2-5}$$

$P_0 = 1$, since it is simply a constant needed for regression; $P_i (i=1, \ldots, 16)$ are the probabilities that the respective dummy variables will be 1. If the regression coefficients are determined from hourly observations, the predicted values will be for one hour later. To generate a n-hour forecast, the first order Markov process is assumed, and one has $\underline{P}(n) = \underline{Z}\ \underline{0}^n$.

A true first order Markov process is one in which the next event depends only on the preceding event and not on the earlier chain of events. Whether a Markov first order process is applicable to meteorological phenomena depends on the extent to which the real world violates the simple model. This model has been shown to hold fairly well (Miller, 1979). Empirical tests such as the one reported here are the only way to examine, indirectly, the validity of the Markov assumption.

The advantages and disadvantages of transforming continuous variables such as temperature into discrete variables (the (0,1) dummies)* are summarized as follows:

Advantages

(1) Probabilities computed directly from regression equations.

(2) Facilitate computations

(3) Probabilities sum to zero.

(4) Probabilities essentially minimize the Brier-Allen P score.

*See Miller, 1964.

Disadvantages

(1) Probabilities are not bounded by 0 and 1.

(2) Transformation from a continuous variable to a discrete variable discards some information.

The first disadvantage can be corrected by normalizing those forecast probabilities that do exceed the (0,1) interval.*

The second disadvantage is accepted as a reasonable trade-off in order to handle the Markov process by simple matrix algebra. This is accomplished by using the vectors of dummy variables, rather than the "true state" vector. In this sense the process is an "equivalent Markov method." It would be impractical, even on large computers, to attempt to compute the true Markov transition matrix for all states, using even a small number of predictors (see Whiton, 1978).

Once the forecast probabilities for each dummy variable are computed, the question arises of how best to use these probabilities to generate a forecast. Miller and Best (1979) have developed a method to determine statistically appropriate threshold probabilities, P*, so that a set of categorical forecasts $\underline{C}$ can be found by

$$\underline{C} = \underline{P} \cdot \underline{P}^* \qquad (2\text{-}6)$$

The C's are either zero or one, indicating which dummy is categorically forecasted.

2.3 EVAPORATION DUCT HEIGHT FORECASTING

The adaptation of the "equivalent Markov method" to the problem of forecasting evaporation duct heights requires first the selection of appropriate meteorological variables from those recorded in the marine surface observations data file. Duct height is calculated from the air, sea and dew point temperatures, and wind speed (Jeske, 1971; Hitney, 1975). The calculated duct height is then added to the selected meteorological variables to form the data base from which the regression coefficients are calculated.

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*See Miller, 1964.

The variables selected to form the predictor set for this present study are listed in Table 1. The weather types are simply the occurrences or non-occurrences of the variable. These 19 variables were then transformed through interval transformation to the 111 dummy variables listed in Table 2 for ocean weather station Echo.

Table 1. Variables in the predictor set.

1. Month
2. Time
3. Wind direction
4. Wind speed
5. Air temperature
6. Dew point
7. Sea surface temperature
8. Air-sea temperature difference
9. Sea level pressure
10. Pressure change (3 m)
11. Total cloud amount
12. Lower cloud amount
13. Duct height - present weather
14. Rain, drizzle, snow
15. Rain showers, snow showers
16. Fog - past weather
17. Rain, drizzle, snow
18. Rain showers, snow showers
19. Fog

Table 2

Month		Time		Wind Direction		Wind Speed	
Jan	(1)	2000-0900	(13)	N-NE	(16)	0-8	(24)
Feb	(2)	0900-1300	(14)	NE-E	(17)	9-11	(25)
Mar	(3)	1300-2000	(15)	E-SE	(18)	12-14	(26)
Apr	(4)			SE-S	(19)	15-17	(27)
May	(5)			S-SW	(20)	18-20	(28)
Jun	(6)			SW-W	(21)	21-23	(29)
Jul	(7)			W-NW	(22)	24-27	(30)
Aug	(8)			NW-N	(23)	28-30	(31)
Sep	(9)					31-99	(32)
Oct	(10)						
Nov	(11)						
Dec	(12)						

Air Temperature		Dew Point		Sea Surface Temperature	
-30. -15.6	(33)	-30. -8.5	(43)	- .1-17.0	(54)
15.7 -16.7	(34)	8.6-11.0	(44)	17.1-17.8	(55)
16.8 -17.8	(35)	11.1-12.5	(45)	17.9-18.3	(56)
17.9 -18.5	(36)	12.6-13.5	(46)	18.4-19.5	(57)
18.6 -19.2	(37)	13.6-15.5	(47)	19.6-21.0	(58)
19.3 -20.0	(38)	15.6-16.5	(48)	21.1-22.7	(59)
20.1 -21.7	(39)	16.6-17.5	(49)	22.8-23.9	(60)
21.8 -24.0	(40)	17.6-18.5	(50)	24.0-25.6	(61)
24.1 -25.5	(41)	18.6-20.5	(51)	25.6-99	(62)
25.6 - 9.9	(42)	20.6-21.5	(52)		
		21.6-99	(53)		

Table 2 (continued)

TA-TS		Sea Level Pressure		Pressure Change	
-30.-4.5	(63)	800-1012	(71)	- 90-1.5	(78)
-4.4-2.8	(64)	1012-1017	(72)	-1.4-1.2	(79)
-2.7-1.6	(65)	1017-1020	(73)	-1.1-0.9	(80)
-1.5-1.0	(66)	1020-1022	(74)	-0.8-0.5	(81)
-0.9-0.5	(67)	1022-1024	(75)	-0.4-0.2	(82)
-0.4-0.0	(68)	1024-1027	(76)	-0.1-0.0	(83)
0.1-0.8	(69)	1027-1100	(77)	0.1-0.3	(84)
0.8-99	(70)			0.4-0.8	(85)
				0.9-1.5	(86)
				1.6-99	(87)

Total Cloud Amount		Lower Cloud Amount		Duct Height	
Clear	(88)	Clear	(92)	0-8	(96)
Scattered	(89)	Scattered	(93)	9-12	(97)
Broken	(90)	Broken	(94)	13-20	(98)
Overcast	(91)	Overcast	(95)	21-90	(99)

Present Weather		Past Weather	
R,L,S	(100)	R,L,S	(106)
No R,L,S	(101)	No R,L,S	(107)
RW,SW	(102)	RW,SW	(108)
No RW,SW	(103)	No RW,SW	(109)
Fog	(104)	Fog	(110)
No Fog	(105)	No Fog	(111)

The intervals chosen were such that the relative frequencies of occurrence were roughly the same (within a factor of 2), with the exception of duct height intervals which were selected on the basis of operational factors. Those intervals for variables such as temperature are latitude-longitude dependent; OWS Charlie therefore has intervals somewhat different than those listed in Table 2 for OWS Echo. The total number of dummies in each case is the same.

The regression coefficients for the equations for each of these dummy variables were calculated using a 10-year data base with observations at three-hour intervals. The probabilities and categorical forecasts were then obtained by matrix multiplication, as shown in Eqs. 2-4 and 2-6.

2.4 DATA BASE

Surface observations for OWS Charlie (52°N, 35°W) and OWS Echo (35°N, 48°W) were used to evaluate the forecast procedure. Ten-year data samples for each OWS were used to calculate the regression coefficients. Independent data samples of about three years for each station were also processed to be used to produce forecasts and skill scores. Each meteorological variable was screened for reasonable values, and observations with any missing variables were discarded.

2.5 EVALUATION PROCEDURE

Evaporation duct height forecasts for three, six, nine, and twelve hours were produced, and then compared to the observed duct heights. Heidke skill scores, threat scores and total percent correct were computed. Since persistence is the best objective forecast technique currently available, it was also tabulated and skill scores computed.

The scores were subjected to a one-way analysis of variance to determine statistically significant differences in the equivalent Markov method and persistence forecast skills.

3. RESULTS

Contingency tables were constructed so that the columns contain the forecasts and the rows contain the observed values of duct heights. Tables 3 through 18 give the cell counts and scores for both ocean weather stations. The "a" tables are the various forecasts using the equivalent Markov forecast procedure; the "b" tables are those for persistence. Both dependent and independent sample results are shown.

The threat score for each diagonal cell and the weighted average for the threat scores were computed (see Appendix); Heidke skill scores for each contingency table also were computed.

3.1 OWS CHARLIE

The Heidke scores for both independent and dependent data samples in Table 19a show that the forecast procedure (F) appears better overall than persistence (P). The averages over all four forecast periods are also larger for F than for P, for both data samples. An analysis of variance* was performed on both samples; the F-values and probabilities are given in Tables 19a and 19b.

The analysis answers the question of whether the forecast average scores really are higher than the persistence average scores. For OWS Charlie, statistically there is a 32% (61%) chance for the "no" answer for the independent (dependent) sample (see Table 19a). Therefore one must reject that answer and accept that the average scores for the forecast procedure and simple persistence are *not* statistically different. Hence the forecast procedure is no better than persistence, based on the Heidke scores.

Threat scores were also subjected to an analysis of variance. Table 19a shows that the average threat score for the independent sample are .579 and .547 for F and P, respectively. The analysis shows no statistical difference between these averages (44% chance of being wrong if one assumes they are different). The dependent sample shows even stronger evidence that the forecast procedure is no better than persistence.

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*The necessary assumption of similar sample variances is clearly satisfied (see Table 17).

3.2 OWS ECHO

Heidke scores are shown in Table 19b for both data samples for OWS Echo. An analysis of variance strongly indicated that the forecast procedure was no better than persistence. The threat scores shown in Table 19b also reveal small F-test values, and high probabilities that these two set of scores are indeed similar.

3.3 DISCUSSION OF RESULTS

The forecast method was compared to persistence via Heidke skill scores and threat scores. Comparisons were made for both the dependent data sample (the data used to generate the forecast equations) and an independent data sample. Data from OWS Charlie (a northern latitude location) and OWS Echo (a midlatitude location) were used to examine the forecast skills for different evaporation duct height distribution (see Sweet, 1979; and Tables 1-16 of this report).

The northern latitude station, Charlie, had a duct height distribution skewed toward the lowest duct height cell (0-8 m). The Heidke skill scores were higher for this station than for Echo, whose distribution was centered about the 12-20 m cell. The same difference was noted for the threat scores (see Tables 19a and 19b). Since the higher duct heights affect more fleet radar systems, Echo's duct height distribution was representative of a more operationally significant distribution type. Therefore, lessor skills of Echo as compared to Charlie is discouraging. This trend was also revealed in the total percent of correct forecasts shown in Tables 20a and 20b.

An analysis of variance comparing the forecast method's skills to the persistence skills revealed that the forecast method was not statistically better than simple persistence. Some forecast-valid periods (i.e., Echo's Heidke skill for the six hour forecast) taken singularly appeared to show that the forecast method was measureably better than persistence. However, when both Heidke and threat scores were considered, no forecast-valid period consistently had higher scores than persistence.

It is concluded that the forecast algorithm as a predictive method is no better than simply forecasting the continuation of current observed duct heights. It appears that further study or development of the forecast method evaluated here would be unproductive unless new developments of the method promise greater skill.

Table 3. OWS Charlie Independent Sample.

3 HR FORECAST

FORECAST

OBSERVED Ht. (m)	0-8	8-12	12-20	>20	TOTAL
0-8	2958	506	21	10	3495
8-12	312	849	80	7	1248
12-20	29	134	50	6	219
>20	13	13	4	8	38
TOTAL	3312	1502	155	31	5000

CORRECT = 77%

SKILL = .507

THREAT
- (0-8) = .762
- (8-12) = .446
- (12-20) = .154
- (>20) = .131
- Average = .652

a

3 HR PERSISTENCE

FORECAST

OBSERVATION Ht. (m)	0-8	8-12	12-20	>20	TOTAL
0-8	2865	384	41	11	3301
8-12	421	690	152	6	1269
12-20	44	156	158	10	368
>20	12	16	13	21	62
TOTAL	3342	1246	364	48	5000

CORRECT = 75%

SKILL = .423

THREAT
- (0-8) = .758
- (8-12) = .378
- (12-20) = .275
- (>20) = .235
- Average = .621

b

Table 4. OWS Charlie Independent Sample.

6 HR FORECAST

FORECAST

OBSERVED Ht.(m)	0-8	8-12	12-20	>20	TOTAL
0-8	947	291	12	0	1250
8-12	151	451	41	1	644
12-20	18	69	12	0	99
>20	6	1	0	0	7
TOTAL	1122	812	65	1	2000

CORRECT = 70%

SKILL = .429

THREAT
(0-8) = .664
(8-12) = .448
(12-20) = .078
(>20) = .0
Average = .560

a

6 HR PERSISTENCE

FORECAST

OBSERVATION Ht.(m)	0-8	8-12	12-20	>20	TOTAL
0-8	1569	258	37	8	1872
8-12	306	327	85	0	718
12-20	51	91	81	4	227
>20	18	7	6	0	31
TOTAL	1944	683	209	12	2848

CORRECT = 69%

SKILL = .369

THREAT
(0-8) = .712
(8-12) = .304
(12-20) = .228
(>20) = .0
Average = .569

b

Table 5. OWS Charlie Independent Sample.

9 HR FORECAST

FORECAST

OBSERVED	Ht.(m)	0-8	8-12	12-20	>20	TOTAL
	0-8	999	297	4	0	1300
	8-12	173	388	21	0	582
	12-20	30	66	8	0	104
	>20	10	4	0	0	14
	TOTAL	1212	755	33	0	2000

CORRECT = 70%

SKILL = .389

THREAT

(0-8) = .660
(8-12) = .408
(12-20) = .062
(>20) = .000
Average = .553

a

9 HR PERSISTENCE

FORECAST

OBSERVATION	Ht.(m)	0-8	8-12	12-20	>20	TOTAL
	0-8	779	144	26	0	949
	8-12	177	160	48	2	387
	12-20	43	47	31	0	121
	>20	12	4	3	1	20
	TOTAL	1011	355	108	3	1477

CORRECT = 66%

SKILL = .303

THREAT

(0-8) = .659
(8-12) = .274
(12-20) = .156
(>20) = .045
Average = .518

b

Table 6. OWS Charlie Independent Sample.

12 HR FORECAST

FORECAST

OBSERVED Ht.(m)	0-8	8-12	12-20	>20	TOTAL
0-8	1066	250	5	0	1321
8-12	208	314	20	0	542
12-20	51	59	2	0	112
>20	17	8	0	0	25
TOTAL	1342	631	27	0	2000

CORRECT = 69%

SKILL = .343

THREAT

(0-8) = .667
(8-12) = .365
(12-20) = .014
(>20) = .000
Average = .552

a

12 HR PERSISTENCE

FORECAST

OBSERVATION Ht.(m)	0-8	8-12	12-20	>20	TOTAL
0-8	2491	603	119	33	3246
8-12	589	546	178	5	1318
12-20	142	158	89	3	392
>20	30	11	2	1	44
TOTAL	3252	1318	388	42	5000

CORRECT = 62%

SKILL = .254

THREAT

(0-8) = .621
(8-12) = .261
(12-20) = .123
(>20) = .011
Average = .482

b

Table 7. OWS Charlie Dependent Sample.

3 HR FORECAST

FORECAST

OBSERVED

Ht.(m)	0-8	8-12	12-20	>20	TOTAL
0-8	861	292	9	5	1167
8-12	125	484	54	2	665
12-20	16	93	46	2	157
>20	4	3	2	2	11
TOTAL	1006	872	111	11	2000

CORRECT = 70%

SKILL = .455

THREAT

(0-8) = .656
(8-12) = .459
(12-20) = .207
(>20) = .100
Average = .547

a

3 HR PERSISTENCE

FORECAST

OBSERVATION

Ht.(m)	0-8	8-12	12-20	>20	TOTAL
0-8	1043	164	26	6	1239
8-12	168	291	78	4	541
12-20	24	82	84	7	197
>20	7	4	6	6	23
TOTAL	1242	541	194	23	2000

CORRECT = 71%

SKILL = .459

THREAT

(0-8) = .725
(8-12) = .368
(12-20) = .274
(>20) = .150
Average = .577

b

Table 8. OWS Charlie Dependent Sample.

6 HR FORECAST

FORECAST

OBSERVED / Ht.(m)	0-8	8-12	12-20	>20	TOTAL
0-8	848	307	16	1	1172
8-12	152	464	41	2	659
12-20	21	105	31	0	157
>20	9	3	0	0	12
TOTAL	1030	879	88	3	2000

CORRECT = 67%

SKILL = .403

THREAT

(0-8) = .626
(8-12) = .432
(12-20) = .145
(>20) = .000
Average = .519

a

6 HR PERSISTENCE

FORECAST

OBSERVATION / Ht.(m)	0-8	8-12	12-20	>20	TOTAL
0-8	965	188	48	11	1212
8-12	188	250	88	8	534
12-20	54	82	77	7	220
>20	10	16	5	3	34
TOTAL	1217	536	218	29	2000

CORRECT = 65%

SKILL = .350

THREAT

(0-8) = .659
(8-12) = .304
(12-20) = .213
(>20) = .050
Average = .505

b

Table 9. OWS Charlie Dependent Sample.

9 HR FORECAST

FORECAST

	Ht.(m)	0-8	8-12	12-20	>20	TOTAL
OBSERVED	0-8	819	329	8	0	1156
	8-12	197	461	24	0	682
	12-20	33	107	10	0	150
	>20	9	3	0	0	12
	TOTAL	1058	900	42	0	2000

CORRECT = 65%

SKILL = .342

THREAT

(0-8) = .587
(8-12) = .411
(12-20) = .055
(>20) = .000
Average = .490

a

9 HR PERSISTENCE

FORECAST

	Ht.(m)	0-8	8-12	12-20	>20	TOTAL
OBSERVATION	0-8	918	199	62	11	1190
	8-12	186	220	111	9	526
	12-20	81	95	75	4	255
	>20	11	11	3	4	29
	TOTAL	1196	525	251	28	2000

CORRECT = 61%

SKILL = .300

THREAT

(0-8) = .625
(8-12) = .265
(12-20) = .174
(>20) = .075
Average = .465

b

Table 10. OWS Charlie Dependent Sample.

12 HR FORECAST

FORECAST

	Ht.(m)	0-8	8-12	12-20	>20	TOTAL
OBSERVED	0-8	832	322	5	0	1159
	8-12	234	420	9	0	663
	12-20	50	106	4	0	160
	>20	13	5	0	0	18
	TOTAL	1129	853	18	0	2000

a

CORRECT = 63%

SKILL = .299

THREAT
(0-8) = .571
(8-12) = .383
(12-20) = .022
(>20) = .000
Average = .472

12 HR PERSISTENCE

FORECAST

	Ht.(m)	0-8	8-12	12-20	>20	TOTAL
OBSERVATION	0-8	901	223	66	11	1201
	8-12	209	225	99	4	537
	12-20	75	98	64	3	240
	>20	11	7	4	0	22
	TOTAL	1196	553	233	18	2000

b

CORRECT = 60%

SKILL = .267

THREAT
(0-8) = .602
(8-12) = .200
(12-20) = .156
(>20) = .000
Average = .450

Table 11. OWS Echo Independent Sample.

3 HR FORECAST

FORECAST

OBSERVED / Ht.(m)	0-8	8-12	12-20	>20	TOTAL
0-8	167	60	15	1	243
8-12	49	134	135	8	326
12-20	14	75	680	178	947
>20	4	14	183	283	484
TOTAL	234	283	1013	470	2000

CORRECT = 63%

SKILL = .447

THREAT

(0-8) = .538
(8-12) = .282
(12-20) = .531
(>20) = .421
Average = .403

a

3 HR PERSISTENCE

FORECAST

OBSERVATION / Ht.(m)	0-8	8-12	12-20	>20	TOTAL
0-8	159	63	17	4	243
8-12	58	140	111	17	326
12-20	18	106	656	167	947
>20	5	19	167	293	484
TOTAL	240	328	951	481	2000

CORRECT = 62%

SKILL = .443

THREAT

(0-8) = .490
(8-12) = .272
(12-20) = .528
(>20) = .436
Average = .459

b

Table 12. OWS Echo Independent Sample.

6 HR FORECAST

FORECAST

OBSERVED Ht.(m)	0-8	8-12	12-20	>20	TOTAL
0-8	157	66	23	0	246
8-12	60	109	141	22	332
12-20	33	88	500	294	915
>20	10	28	162	307	507
TOTAL	260	291	826	623	2000

a

CORRECT = 54%

SKILL = .330

THREAT

(0-8) = .449
(8-12) = .212
(12-20) = .402
(>20) = .373
Average = .370

6 HR PERSISTENCE

FORECAST

OBSERVATION Ht.(m)	0-8	8-12	12-20	>20	TOTAL
0-8	145	58	34	3	240
8-12	46	110	127	38	321
12-20	33	115	549	227	924
>20	5	34	235	241	515
TOTAL	229	317	945	509	2000

b

CORRECT = 52%

SKILL = .295

THREAT

(0-8) = .447
(8-12) = .208
(12-20) = .415
(>20) = .307
Average = .358

Table 13. OWS Echo Independent Sample.

9 HR FORECAST

FORECAST

OBSERVED / Ht.(m)	0-8	8-12	12-20	>20	TOTAL
0-8	166	60	33	1	260
8-12	86	98	117	39	340
12-20	48	106	394	337	885
>20	20	32	170	293	515
TOTAL	320	296	714	670	2000

CORRECT = 48%

SKILL = .261

THREAT

(0-8) = .400
(8-12) = .182
(12-20) = .596
(>20) = .328
Average = .422

a

9 HR PERSISTENCE

FORECAST

OBSERVATION / Ht.(m)	0-8	8-12	12-20	>20	TOTAL
0-8	85	48	22	6	161
8-12	28	68	87	31	214
12-20	36	65	375	177	653
>20	7	23	198	161	389
TOTAL	156	204	682	375	1417

CORRECT = 49%

SKILL = .235

THREAT

(0-8) = .366
(8-12) = .194
(12-20) = .390
(>20) = .266
Average = .325

b

Table 14. OWS Echo Independent Sample.

12 HR FORECAST

FORECAST

OBSERVED Ht.(m)	0-8	8-12	12-20	>20	TOTAL
0-8	156	57	37	2	252
8-12	106	80	103	40	329
12-20	52	134	387	326	899
>20	23	41	184	272	520
TOTAL	337	312	711	640	2000

CORRECT = 45%

SKILL = .222

THREAT

(0-8) = .360
(8-12) = .142
(12-20) = .316
(>20) = .305
Average = .291

a

12 HR PERSISTENCE

FORECAST

OBSERVATION Ht.(m)	0-8	8-12	12-20	>20	TOTAL
0-8	67	36	19	6	128
8-12	23	45	63	25	156
12-20	14	59	259	127	459
>20	11	24	126	111	272
TOTAL	115	164	467	269	1015

CORRECT = 47%

SKILL = .230

THREAT

(0-8) = .380
(8-12) = .163
(12-20) = .388
(>20) = .258
Average = .317

b

Table 15. OWS Echo Dependent Sample.

3 HR FORECAST

FORECAST

Ht.(m)	0-8	8-12	12-20	>20	TOTAL
OBSERVED 0-8	120	89	26	1	236
8-12	57	165	159	11	392
12-20	20	94	639	133	886
>20	12	22	209	243	486
TOTAL	209	370	1033	388	2000

CORRECT = 58%

SKILL = .383

THREAT

(0-8) = .369
(8-12) = .276
(12-20) = .497
(>20) = .385
Average = .417

a

3 HR PERSISTENCE

FORECAST

Ht.(m)	0-8	8-12	12-20	>20	TOTAL
OBSERVATION 0-8	124	84	18	10	236
8-12	66	170	130	26	392
12-20	27	118	561	180	886
>20	13	23	190	260	486
TOTAL	230	395	899	476	2000

CORRECT = 56%

SKILL = .359

THREAT

(0-8) = .362
(8-12) = .275
(12-20) = .458
(>20) = .370
Average = .390

b

Table 16. OWS Echo Dependent Sample.

6 HR FORECAST

FORECAST

OBSERVED

Ht.(m)	0-8	8-12	12-20	>20	TOTAL
0-8	116	85	43	1	245
8-12	79	173	150	22	424
12-20	35	117	533	184	869
>20	16	35	198	213	462
TOTAL	246	410	924	420	2000

CORRECT = 52%

SKILL = .303

THREAT

(0-8) = .309
(8-12) = .262
(12-20) = .423
(>20) = .318
Average = .352

a

6 HR PERSISTENCE

FORECAST

OBSERVATION

Ht.(m)	0-8	8-12	12-20	>20	TOTAL
0-8	136	78	48	11	273
8-12	66	168	151	38	423
12-20	49	138	485	181	853
>20	17	37	182	215	451
TOTAL	268	421	866	445	2000

CORRECT = 50%

SKILL = .291

THREAT

(0-8) = .336
(8-12) = .248
(12-20) = .393
(>20) = .316
Average = .337

b

Table 17. OWS Echo Dependent Sample.

9 HR FORECAST

FORECAST

OBSERVED Ht.(m)	0-8	8-12	12-20	>20	TOTAL
0-8	110	84	44	2	240
8-12	106	148	150	28	432
12-20	45	138	484	223	890
>20	22	27	192	197	438
TOTAL	283	397	870	450	2000

CORRECT = 47%

SKILL = .239

THREAT

(0-8) = .286
(8-12) = .217
(12-20) = .379
(>20) = .285
Average = .307

a

9 HR PERSISTENCE

FORECAST

OBSERVATION Ht.(m)	0-8	8-12	12-20	>20	TOTAL
0-8	147	72	46	17	282
8-12	64	140	155	39	398
12-20	49	144	475	215	883
>20	13	44	205	175	437
TOTAL	273	400	881	446	2000

CORRECT = 47%

SKILL = .236

THREAT

(0-8) = .360
(8-12) = .213
(12-20) = .368
(>20) = .247
Average = .309

b

Table 18. OWS Echo Dependent Sample.

12 HR FORECAST

FORECAST

OBSERVED Ht.(m)	0-8	8-12	12-20	>20	TOTAL
0-8	111	71	44	7	233
8-12	109	136	151	26	422
12-20	56	134	521	202	913
>20	26	27	189	190	432
TOTAL	302	368	905	425	2000

CORRECT = 48%

SKILL = .246

THREAT

(0-8) = .262
(8-12) = .208
(12-20) = .402
(>20) = .285
Average = .320

a

12 HR PERSISTENCE

FORECAST

OBSERVATION Ht.(m)	0-8	8-12	12-20	>20	TOTAL
0-8	126	68	61	15	270
8-12	70	134	154	42	400
12-20	39	139	452	221	851
>20	28	46	211	194	479
TOTAL	263	387	878	472	2000

CORRECT = 45%

SKILL = .219

THREAT

(0-8) = .309
(8-12) = .205
(12-20) = .354
(>20) = .256
Average = .295

b

Table 19. Ocean Weather Station Charlie.

HEIDKE SCORES

INDEPENDENT F	INDEPENDENT P	HR	DEPENDENT F	DEPENDENT P
.507	.483	3	.455	.459
.429	.369	6	.403	.356
.389	.303	9	.342	.300
.343	.254	12	.299	.267
.417	.352	Average	.374	.345
.0036	.0074	σ^2	.0035	.0053
1.144		F-Value	.291	
.32		Probability	.61	

THREAT SCORES

INDEPENDENT F	INDEPENDENT P	HR	DEPENDENT F	DEPENDENT P
.652	.621	3	.547	.577
.560	.569	6	.519	.505
.553	.518	9	.490	.465
.552	.482	12	.472	.450
.579	.547	Average	.507	.499
.0018	.0027	σ^2	.0008	.0024
.667		F-Value	.055	
.44		Probability	.82	

a

Table 19. Ocean Weather Station Echo.

HEIDKE SCORES

INDEPENDENT			DEPENDENT	
F	P	HR	F	P
.447	.443	3	.383	.359
.330	.295	6	.303	.291
.261	.235	9	.239	.238
.222	.230	12	.246	.219
.315	.300	Average	.292	.276
.0073	.0074	σ^2	.0033	.0029
.0414		F-Value	.1222	
.84		Probability	.74	

THREAT SCORES

INDEPENDENT			DEPENDENT	
F	P	HR	F	P
.403	.459	3	.417	.390
.370	.358	6	.352	.337
.422	.325	9	.309	.309
.291	.317	12	.320	.295
.371	.364	Average	.349	.332
.0025	.0032	σ^2	.0017	.0013
.0239		F-Value	.2724	
.88		Probability	.62	

b

Table 20

Ocean Weather Station Charlie

PERCENT CORRECT

INDEPENDENT			DEPENDENT	
F	P	HR	F	P
77	75	3	70	71
70	69	6	67	65
70	66	9	65	61
69	62	12	63	60

a

Ocean Weather Station Echo

INDEPENDENT			DEPENDENT	
F	P	HR	F	P
63	62	3	58	56
54	52	6	52	50
48	49	9	47	47
45	47	12	48	45

b

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APPENDIX
THREAT AND SKILL SCORES DEFINITIONS

THREAT SCORES

Consider a 2x2 contingency table.

		Forecast		
		F_1	F_2	Totals
Observed	O_1	d_1	b	R_1
	O_2	c	d_2	R_2
Totals		c_1	c_2	T

The threat score is defined as

$$TS = \frac{d_1}{d_1 b+c} .$$

This score examines the ratio of correct forecasts (d_1) to the sum of correct and incorrect ($d+b+c$). If $b=c=0$, then $TS=1$. Therefore $0 \leq TS \leq 1$.

Notice that since $R_1=d_1+b$ and $c_1=d_1+c$,

$$TS = \frac{d_1}{R_1+c_1-d_1} .$$

Using this formula, threat scores for nxn contingency tables can be computed for each diagonal element (d_i, $i=1,\ldots,n$). For a (nxn) contingency table, n threat scores are computed.

To compare threat scores for two contingency tables, a weighted average is computed.

$$(TS)_1 = \frac{d_1}{R_1+c_1-d_1}$$

$$(TS)_2 = \frac{d_2}{R_2+c_2-d_2}$$

Then $(TS)_A$, the weighted average, is defined by

$$(TS)_A = \left(\frac{R_1+c_1}{2}\right)(TS)_1 + \left(\frac{R_2+c_2}{2}\right)(TS)_2.$$

SKILL SCORES

Heidke skill scores are defined for (2x2) contingency tables as follows.

		F_1	F_2	Total
Observations	0_1	d_1	d	R_1
	0_2	c	d_2	R_2
	Total	c_1	c_2	T

$$S = \frac{X-C}{T-C}$$

where

$$X = d_1+d_2$$

$$C = \frac{(R_1C_1)}{T} + \frac{(R_2C_2)}{T}$$

For a (nxn) contingency table the generalized formula is

$$S = \frac{X-C}{T-C}$$

$$X = \sum_{i=1}^{n} d_i$$

and

$$C = \frac{1}{T}\sum_{i=1}^{n}(R_iC_i).$$

The Heidke skill score compares total correct forecasts with the expected total correct forecasts, as determined from a chance selection procedure.

For example, the chance that any single forecast event will fall in the first column is $(\frac{C_1}{T})$. The chance that any single observed event will fall in the first row is $(\frac{R_1}{T})$. Therefore, the chance that any single forecast-observation event will fall in the first diagonal cell (cell d_1) is $(\frac{C_1}{T})$ $(\frac{R_1}{T})$, and the expected number of events to fall in cell d_1 is the

$$(\frac{C_1}{T}) x (\frac{R_1}{T}) \ (T) = (\frac{C_1 R_1}{T}) \ .$$

Therefore

$$C = \frac{1}{T} \sum_{i=1}^{n} (C_i R_i),$$

is simply the total expected number of events to fall on the diagonal elements.

The skill score then is the ratio of actual minus expected to total minus expected.

If x=c, than s=0, and thus the forecast method shows no skill better than random chance. If X=T, S=1; the forecast is perfect. (Notice it is possible to get negative skills (i.e., X<C), which means that chance beats the forecast method.)

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